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Retraction

Retracted: Extraction and Analysis of Influencing Factors of Scientific and Technological Ability Improvement of University Teachers Based on Deep Learning Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] A. Wang and W. Yan, "Extraction and Analysis of Influencing Factors of Scientific and Technological Ability Improvement of University Teachers Based on Deep Learning Model," *Advances in Multimedia*, vol. 2022, Article ID 3922342, 12 pages, 2022.

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Research Article

Extraction and Analysis of Influencing Factors of Scientific and Technological Ability Improvement of University Teachers Based on Deep Learning Model

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In order to improve the development and construction level of colleges and universities and help teachers improve their scientific and technological abilities, a model based on deep learning model for the extraction and analysis of factors affecting the improvement of college teachers' scientific and technological abilities was proposed. This article analyzes the data of teaching evaluation and finds that the text contains students' subjective understanding of teachers' teaching quality defects. By extracting key words from students' teaching evaluation texts and combining with the teaching evaluation indexes, a teaching evaluation label system integrating teaching evaluation texts is designed. In order to find the defects of teachers' teaching ability, this article, based on the principle of data portrait, combines the characteristics of teachers' personal basic information, curriculum information, teaching evaluation information, and social relations to portrait teachers. The experimental results show that the F1 value extracted from the evaluation labels fluctuates in the evaluation text data of different colleges, with the lowest value of 91.7% in the School of Statistics and the highest value of 95.8% in the School of Foreign Languages. The algorithm in this article has a higher F1 value of the evaluation label vector extracted from the evaluation text of different grades. F1 values showed a trend of gradient decline with the increase of grade, and the decreasing range became bigger and bigger. Conclusion. The constructed teacher portraits are more accurate and effective, and provide a comprehensive and effective data model for teaching ability improvement method recommendation strategy.

1. Introduction

The 21st century is the century of human resource capacity building. Since APEC held the Summit on Human Capacity Building, the Human Capacity Building has attracted widespread attention. In the 21st century, science and technology are advancing rapidly, the trend of economic globalization is further accelerating, and the "new economy" supported by knowledge and high-tech industry is emerging. Mastering and applying new knowledge and technology is the key to everyone's development [1]. In the 21st century, the development of a person, an organization, or a country is no longer determined by wealth, but by ability. Ability is the source of wealth, resources, and competitive advantage. Attaching importance to human resource capacity building is related to the improvement of China's comprehensive national strength and international competitiveness, as well as the long-term development of China's reform and opening up a socialist modernization [2]. Only by strengthening human resource capacity building and comprehensively improving the quality of the people can we inject inexhaustible impetus into economic and social development. Only by changing the production mode of excessive consumption of material resources can the economy and society achieve sustainable development. Therefore, human society in the 21st century has entered an era centered on human ability.

Since ancient times, universities have been the place where human wisdom and knowledge are generated, gathered,

radiated, and spread to the outside world. At present, universities, as the main field of cultivating high-quality talents, are also the main field of national human resource capacity construction [3]. As a pioneer in universities, research universities shoulder special mission and responsibility in the strategy of building an innovative country and a powerful country with talents. Teachers in research universities are rare high-level talents with stronger comprehensiveness, initiative, creativity, and plasticity than ordinary human resources. Therefore, the faculty capacity building of research universities plays an exemplary role in the national human resource capacity building system.

2. Literature Review

Qi, S. et al. proposed that in the era of big data, the evaluation of teachers can not only carry out quantitative and qualitative evaluation, but also provide effective feedback to teachers. Targeted improvement measures are formulated to promote the improvement of teachers' teaching quality and teaching level [4]. Zy, A et al. constructed a fuzzy comprehensive evaluation model by using analytic hierarchy process. On the subjective basis, combined with logical mathematical methods, the weight of evaluation indicators can be reasonably determined [5]. Sena, A. et al.'s general evaluation of teaching quality of college teachers. The technical means of fuzzy structure element using intuitionistic fuzzy multiattribute decision-making was adopted, and the evaluation model of college teachers' ability was constructed, and its feasibility was verified [6]. Zheng, S. et al. analyzed the factors that may affect the teaching quality, established the teaching quality evaluation index system, proposed the comprehensive evaluation method combining hierarchical analysis and multiattribute fuzzy decision making, so as to transform the qualitative analysis into quantitative analysis, and verified the usability in the teaching of tourism management specialty [7]. Leeabai, N. et al. proposed a set of mixed methods for feedback on teachers' teaching effectiveness [8]. Macleod, A. et al. believe that academic evaluation in institutions of higher learning is often based on examination results, which leads to the gradual formation of the bad habit of "focusing on learning whatever is tested", which is very detrimental to the cultivation of students' independent thinking ability. Therefore, a new teacher evaluation system should be constructed, which should take students as the main body, fully stimulate students' subjective initiative and promote the change of their learning attitude [9]. Xu, E. et al. used expert interview method and questionnaire survey method to determine the indicators. Their research results are as follows: (1) a teaching quality evaluation system was constructed, including 4 first-level indicators, 10 second-level indicators, and 30 third-level indicators; (2) Practical research on teaching quality evaluation system shows [10]. Wang, X. et al. proposed to build a teaching quality evaluation system for college teachers from six aspects. They are: the scope of teaching work, teaching attitude, teaching content, teaching methods, teaching characteristics, and teaching effects of college teachers are defined [11].

This study enriches the research of recommendation system in the promotion strategy of teachers' teaching ability. In the traditional student evaluation system, teachers often only get a final evaluation score, which does not give full play to the effective feedback of student evaluation. In the research of the recommendation system for the improvement of teaching ability, some scholars have designed the corresponding recommendation system for teachers to recommend learning objects, learning resources, ability improvement path, and other relevant information, so as to improve the teaching ability of college teachers. However, the above information recommendation does not closely focus on the specific defects found by teachers in teaching quality assessment.

3. Research Methods

3.1. Concept of Deep Learning. The concept of deep learning is derived from relevant researches in the field of computer science, artificial intelligence technology, and artificial neural network, and it is a new machine learning algorithm compared with simple machine learning [12]. Deep learning adopts multilayer structure such as input layer, hidden layer, and output layer similar to neural network. By means of feature combination, the original input is transformed layer by layer into shallow feature, middle feature, and high-level feature until the final task target. Later, deep learning expanded to the field of education. Some scholars focused on the learning process and learning style of teachers and the value of deep learning for teacher development. Deep learning is based on understanding learning. Learners are able to critically learn new ideas and facts, integrate them into the original cognitive structure, make connections among many ideas, and transfer existing knowledge to new situations to make decisions and solve problems. In recent years, deep learning has become one of the research hotspots in the field of education.

3.2. Construction of Teaching Evaluation Label System

3.2.1. Comment on the Source of the Teaching Text Set. The set of student teaching evaluation texts used in this research is derived from the real data of a university undergraduate online teaching evaluation system. In 2018, the university rebuilt a new student evaluation system by summarizing the shortcomings of the previous evaluation system, which has significantly improved the integrity and effectiveness of data.

A university has been implementing the teaching concept of "student-centered", and its teaching evaluation index system focuses on assessing the teaching quality of teachers from five aspects: teaching attitude, teaching content, teaching method, learning harvest, and teaching effect. The curriculum of a certain university includes four kinds of courses: general course, bilingual course, experiment (practice) course, and physical education course. Four sets of different evaluation indicators are designed according to different courses. Take the general theory course as an example, as shown in Table 1 below.

Table 1: Undergraduate teaching evaluation indicators (general courses).

Number	Evaluation indicators
1	The teacher is dignified in appearance, careful in words, and behavior
2	The teacher was patient in answering our questions
3	The teacher is willing to provide us with help in study and other aspects
4	The teacher clearly told the teaching content, teaching requirements, and assessment methods of the course at the beginning of the semester
5	Teachers provide rich teaching resources (including lesson plans, courseware, network resources, auxiliary learning materials, equipment or equipment, etc.) to assist teaching
6	Teachers will correct assignments or lab reports in a timely manner and give feedback
7	The teacher will introduce cutting edge knowledge relevant to the course or major
8	The teacher's courseware (or blackboard writing) is neat, beautiful, and standard
9	The teacher's class is lively and interesting and can attract our attention
10	The teacher often encourages us to speak and discuss in class, and the class atmosphere is active
11	I can use the knowledge and methods learned in this course to solve practical problems
12	I look forward to this class every time
13	I will pay attention to the developments in the field related to the course or participate in related activities
14	The teacher has a great influence on my future study and life
15	I would recommend other students to take this course
16	I would like to take other courses offered by the teacher

Table 2: Features of unstructured student evaluation texts.

Number	Category	Features
1	Text words	Often use idioms or idioms related to a particular field to express an opinion about a particular field
2	Text content	The number of topics contained in the text varies, and there may be cases where one text represents multiple related topics
3	Language specification	The language expression is simple and random, and the sentence structure is complex and diverse

When students conduct online teaching evaluation, they need to evaluate teachers according to their teaching quality. There are two ways of evaluation: teaching evaluation index and subjective writing suggestions. The scoring of teaching evaluation indicators means that students score according to these 16 indicators, and the scoring options are divided into four options: "Very dissatisfied", "dissatisfied", "satisfied", and "very satisfied" [13]. After collecting the evaluation indicators of all students, the student evaluation system will calculate the weighted average of the scores of all students of the course, and regard it as the final evaluation score of the teacher in the student evaluation activities of the course. For students' teaching comments, teaching evaluation staff will check the content of the comments, and manually screen out some bad situations, which will be anonymous criticism in the assessment meeting. Most teachers can only get one final result of teaching evaluation, and there is no data mining and analysis for text comments.

3.2.2. Analysis of Teaching Text Data. Data mining in different fields varies according to the characteristics of data, especially in the field of teaching ability improvement. Student evaluation text is a kind of unstructured text data, which cannot be analyzed and processed directly by traditional statistical methods. This article summarizes the characteristics of the unstructured text data of student evaluation of teaching, and the summary results are shown in Table 2.

Before mining and analyzing the text data, the text data must be cleaned and preprocessed. Removing noise in text can improve the accuracy of text feature extraction. In the study of students' evaluation of teaching text, it is found that the evaluation of teaching text with analytical value should meet the "description word+degree adverb", such as "homework more". In order to quickly complete the student evaluation, some students fill in the evaluation text with very nonstandard words, or even directly do not fill in. Therefore, the original evaluation text library may contain some invalid evaluation text. These invalid evaluation texts will affect the subsequent analysis and processing. Therefore, in order to improve the quality of text data, this part of invalid text needs to be cleaned and filtered [14].

As shown in Figure 1, this article designs the following processing steps based on the above characteristics of invalid student teaching evaluation texts.

Step 1. Word segmentation.

In this article, jieba word segmentation in HANLP is applied to the word segmentation of the text.

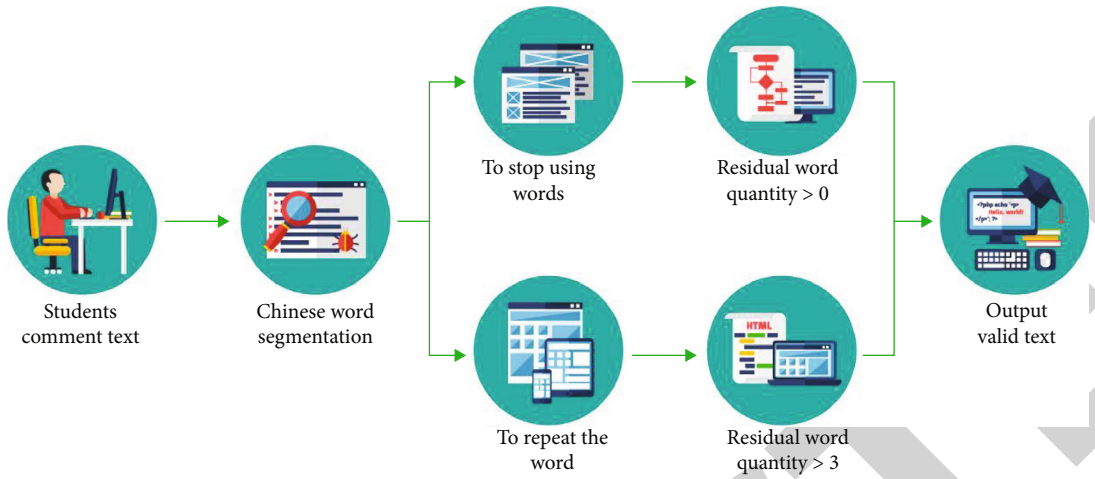

Figure 1: Review teaching text cleaning process.

Step 2. Filter invalid text after removing repeated words.

Words that appear more frequently in the same text are considered as repeated words. After word segmentation, the operation of removing repeated words is carried out on the student's teaching comment text. If the number of remaining words is less than 2 after removing repeated words, the teaching comment text is judged as invalid text and then filtered out. This step can effectively filter the type 1 invalid text.

Step 3. Remove stop words and filter invalid text.

Stop words are words or symbols irrelevant to the content of the text, which will have a negative impact on the effect of word segmentation. Such as the modal particle "ba" and meaningless punctuation marks. This article adopts the stop word list published by the Chinese Academy of Sciences, and deletes the stop words in the text according to the matching of the stop word list [15]. If the number of remaining words in the text after removing the stop word is 0, the text will be judged as invalid and filtered out. This step can effectively filter type 2 invalid text.

After the above cleaning process, a total of 450,636 valid student evaluation texts were obtained, which will be used for subsequent research and experiments.

3.2.3. Definition of Teaching Evaluation Label. In section 3.2.1, this article introduces 16 evaluation indicators of general courses of a certain university. Therefore, based on the teaching evaluation index content of general courses formulated by a university, this section first analyzes the teaching quality-related content of the index and constructs the initial teaching evaluation label, as shown in Table 3.

(1) Initial teaching evaluation label. As can be seen from Table 3, there are 5 first-level labels and 20 second-level labels in the initial evaluation of teaching. The 16 teaching evaluation indicators of a university were decomposed into 20 secondary labels, and then the 20 secondary labels were associated with five primary labels.

Table 3: Initial teaching evaluation label.

Grade 1 evaluation teaching label	Grade 2 evaluation teaching label
Teaching attitude	Teacher moral cultivation
	Sufficient preparation
	Complete lesson plans
	Homework correction
	After-school tutoring
	Concerned about the students
Teaching content	Content properly
	Lead to inspiration
	Be innovative
	Rich knowledge
Teaching level	Proficient in teaching
	Easy to understand
	Class schedule
Teaching methods	Answer questions
	Teaching progress
	Homework assignments
	Interaction and communication
Teaching effect	Simple things come out
	Develop capacity
	Learning gain

(2) Integrate teaching evaluation labels with teaching evaluation texts. Through the observation of the teaching evaluation text set, it is found that there are some potential teaching evaluation labels in the teaching evaluation text that have nothing to do with the teaching evaluation index. For example, the assessment method of teachers' courses, moral cultivation, political thought, and other labels [16]. Therefore, this article takes students as the center, through processing and analyzing the evaluation and teaching text of students, further excavates the evaluation and teaching labels that students are more concerned about, and achieves the

Name: Key word extraction procedure of student evaluation teaching text
Input: Collection of student comments on teaching texts
Part of speech set
Word frequency threshold
Output: Keyword: Set of keywords
Methods and steps:
Step1: Classify words for each document in the student text set, and count the part of speech and word frequency of each word.
Step2: Select a word in the word set. If the part of speech of the word is in part of speech p and the word frequency is greater than the word frequency threshold, add it to the keyword set. If it is smaller than the word frequency threshold, continue the statistics.
Step3: Repeat the second step until all text processing is completed.

Algorithm 1: Key words extraction steps of student evaluation teaching text.

purpose of supplementing and perfecting the evaluation and teaching labels from the perspective of students.

In order to dig out the evaluation and teaching labels that students are potentially concerned about, this article firstly extracts the keywords contained in the evaluation and teaching text set, then summarizes the extracted keywords, and finally supplements and adjusts the initial evaluation and teaching labels according to the conclusion, forming a student-centered evaluation and teaching label system. Specific methods are as follows:

Keyword extraction. In this article word frequency and part of speech are taken as the basic features of subject words in the extracted teaching evaluation texts. It is assumed that the set of students' teaching evaluation texts is $C = \{A_1, A_2, A_3, \cdots, A_n\}$ where n represents the number of teaching comments and A is a teaching comments in the set of teaching comments. w is a word in the document p is the part of speech of the word tf is the frequency of the word and α is the frequency threshold of the keyword.

The keyword extraction algorithm in this article contains the following three interface methods, of which method 1 and method 2 are realized through the interface in Hanlp.

Method 1. ssplit_word(), input all the texts in the evaluation text set one by one, and output the final word segmentation result to the word set W.

Method 2. pos_tag(), used with split_word_s(), outputs the (w, p) set of tuples corresponding to the word and its part of speech.

Method 3. Init () method, input is word set W and word part binary set (w, p), output is word, word part and word frequency triplet set (w, p, tf). Algorithm 1 shows the key words extraction steps of students' teaching evaluation texts.

In this article, the threshold value of α is set as 200, and 450, 636 students' teaching evaluation texts obtained after text preprocessing in the previous section are processed by keyword extraction method. Finally, there are 867 keywords in key_word.

Keyword summary. This article analyzes the key words in key_word from the word semantics and finds the teacher's language ability personal quality teacher-student relationship and other evaluation labels that students care about. Some examples are shown in Table 4

The teaching evaluation label system from the perspective of students. The teaching evaluation label integrated with students' teaching evaluation text can better reflect students' subjective thoughts. Based on the conclusion of keywords, this article constructed the final teaching evaluation label system from the perspective of students, as shown in Table 5.

As can be seen from the above table, compared with the initial teaching evaluation label, the teaching evaluation label from the perspective of students adds four first-level labels: "Classroom atmosphere", "overall evaluation", "personal quality", and "teacher-student relationship". Finally, there are nine first-level teaching evaluation labels, which are marked as $\mathrm{Tag}_i (i = 1 \cdots 9)$. Some labels were added in the secondary evaluation labels, and finally there were 30 secondary labels, which made the evaluation labels more abundant.

3.3. Construction of Teacher Portraits

3.3.1. Teacher Portrait Index System. The implementation of the teacher user portrait construction strategy based on multilevel association needs to consider not only the teaching evaluation results, but also the individual characteristics of the teacher, the course characteristics of the professor and the social relationship. Otherwise, the accuracy of the recommendation will be affected to a large extent. Therefore, the key to recommendation is to correlate all kinds of information of teachers and construct teacher portraits [17]. According to the analysis of students' teaching evaluation data and the recommendation of teaching ability improvement methods, the index system of teacher portrait is preliminarily constructed. The index system mainly includes the characteristics of teachers' evaluation of teaching results, teachers' individual characteristics, teachers' curriculum characteristics, and teachers' social relations. The index architecture of teacher portrait is shown in Figure 2. As can be seen from the figure, the individual characteristics of teachers mainly include the professional title, gender, age, and number of courses taught by teachers. The characteristics of teacher evaluation results mainly include teacher evaluation scores and evaluation labels. The characteristics of teaching courses mainly include course types, number of students, and class hours. Teacher's social relationship refers to the degree of similarity among teachers.

Table 4: Example of keyword induction section.

Inductive label	Keywords
Teacher's language ability	Mandarin, English, pronunciation, voice, etc
Personal qualities	Appearance, dress, pretty, decent, cool, amiable, etc
Relationship between teachers and students	Respect, care, love, abuse, coercion, etc
Professional quality	Knowledgeable, professional, skilled, dry goods, etc
Teaching attitude	Serious, responsible, careful, etc
Course assessment, assessment difficulty, etc	Check-in, final, exam, paper, point arrival, etc

Table 5: Teaching evaluation label system from the perspective of students.

Number	Grade 1 evaluation teaching label	Grade 2 evaluation teaching label
Tag_1	Teaching attitude	Teacher moral cultivation
		Sufficient preparation
		Complete lesson plans
		Homework correction
		After-school tutoring
		Concerned about the students
Tag_2	Teaching content	Content properly
		Lead to inspiration
		Be innovative
Tag_3	Teaching level	Rich knowledge
		Proficient in teaching
		Easy to understand
Tag_4	Teaching methods	Language ability
		Class schedule
		Answer questions
		Progress of teaching
		Homework assignments
Tag_5	Teaching effect	Interaction and communication
		Simple things come out
		Develop capacity
		Learning gain
Tag_6	Classroom atmosphere	Classroom atmosphere
		Learning atmosphere
Tag_7	Overall evaluation	Overall evaluation
Tag_8	Personal accomplishment	Dress up
		Personality character
		Appearance makeup
Tag_9	Relationship between teachers and students	Treat students
		Answering questions after class
		Communication and interaction

3.3.2. Model Construction of Teacher Portraits. The portrait constructed in this article is considered from a multilevel perspective. Only by comprehensively analyzing multiple levels of teacher information and depicting a teacher as completely as possible, rather than analyzing only from one dimension, can the portrait painted meet the requirements of teaching ability improvement method recommendation. Teacher portrait can not be analyzed from a single level, but to be able to express the tendency of teachers in different aspects, can fully express the needs of teachers in the method of teaching ability improvement, the teacher portrait constructed must have a more obvious sense of hierarchy, intuitive, and clear information expression is convenient for computer processing and calculation.

The teacher portrait proposed in this article includes four aspects: the individual characteristics of teachers, the characteristics of teachers teaching courses, the characteristics of teachers' evaluation of teaching results, and the social

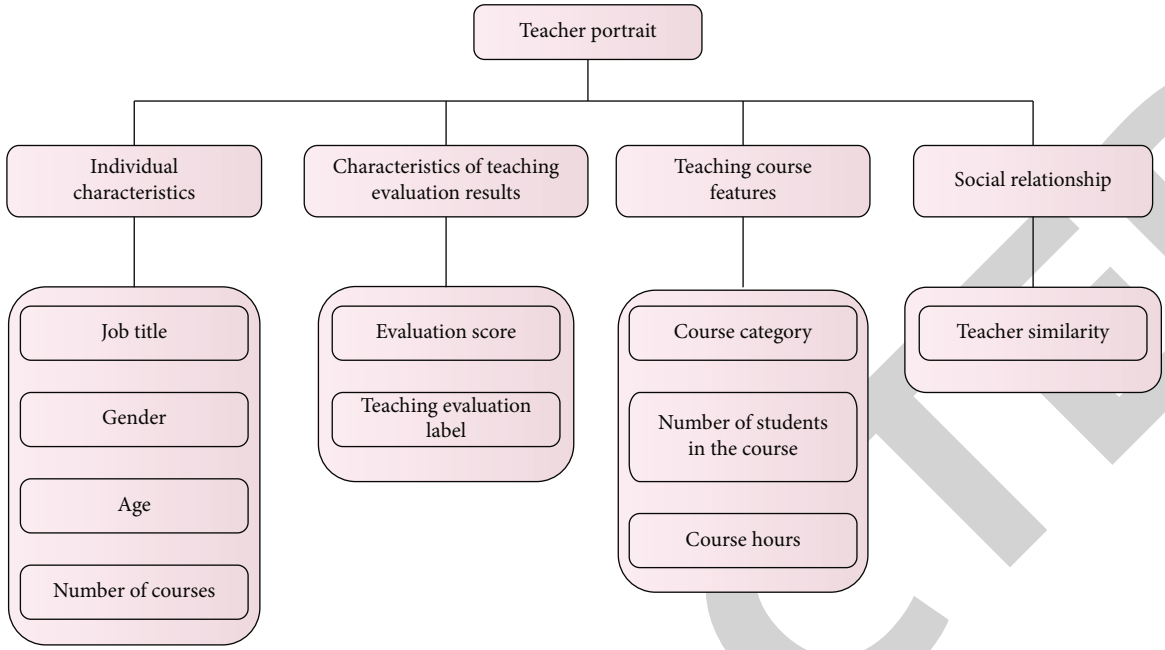

Figure 2: Index architecture diagram of teacher portrait.

relations of teachers. Due to the need to accurately recommend teachers' teaching ability improvement methods, the similarity between teachers can indicate teachers' tendency to make up for defects, which will affect teachers' choice of teaching ability improvement methods, the richness of teacher portraits, and the accuracy of teaching ability improvement method recommendation. The similarity between teachers also needs to be added into the model of teacher portrait, and at the same time, a teacher portrait with a relatively clear structure is described by combining other features.

This article defines a quad TeacherModel = (IndividualCharacter, base, CourseInfo, EvaluationResults) to represent a teacher picture information. See Figure 3.

As shown in Figure 3, IndividualCharacter represents the model of teachers' individual characteristics, EvaluationResults represents the model of teachers' evaluation of teaching results, CourseInfo represents the model of teachers' teaching courses, and Relation represents the model of teachers' social relations. IndividualCharacter consists of many static variables obtained from the educational administration information system. EvaluationResults are composed of teachers' evaluation scores and EvaTags, which are obtained from the evaluation labeling system proposed in this article. CourseInfo is composed of static attributes for the course taught by the instructor. Relation is obtained by calculating Similarity among teachers.

3.3.3. Generation of Teacher Portraits. Teacher painting is based on the Teacher model into the line, which includes the Teacher a special body IndividualCharacter, EvaluationResults, CourseInfo, and the generation of teacher's social Relation [18]. Since both the individual characteristics of teachers and the curriculum characteristics of teachers are directly obtained from the educational administration information system, this article does not elaborate on the generation process. The following is a detailed introduction of the characteristics of teacher evaluation results and the generation method of teachers' social relationship features [19].

In the characteristics of teacher result, there are two attributes: teaching evaluation score and teaching evaluation label vector. The score is obtained by the statistics of the evaluation system and can be directly captured from the student evaluation system. The evaluation label vector contains the first-level evaluation label vector and the second-level evaluation label vector. MainTag is used as the first-level evaluation label vector of teachers, and weight is used to represent the degree of compliance of teachers on this first-level evaluation label. EvaTag is also used as the vector of teachers' second-level evaluation labels, and the degree of compliance on each second-level evaluation label is denoted by weight. Through the above method, the overall evaluation tag vector can be represented by the binary group (MainTag and EvaTag) composed of these two vectors [20]. Since there is a subordinate relationship between the second-level evaluation label vector and the first-level evaluation label vector, the sum of the weight value of the second-level label vector to which the first-level evaluation label belongs can be used as the weight value of the first-level evaluation. Therefore, the specific generation steps of EvaTag vector will be described in detail below.

In most recommendation systems, the most important is the model construction based on recommendation ontology, which accounts for about 70%, while the recommendation algorithm only accounts for about 30%. Therefore, EvaTag vector is an important factor in this article and also the basis for recommending teaching ability improvement methods. In this article, the label features of teachers' second-level teaching evaluation are mainly used to describe teachers in the form of keyword extraction from students' teaching evaluation texts. In the teaching evaluation label system introduced in this article, a total of 30 secondary teaching

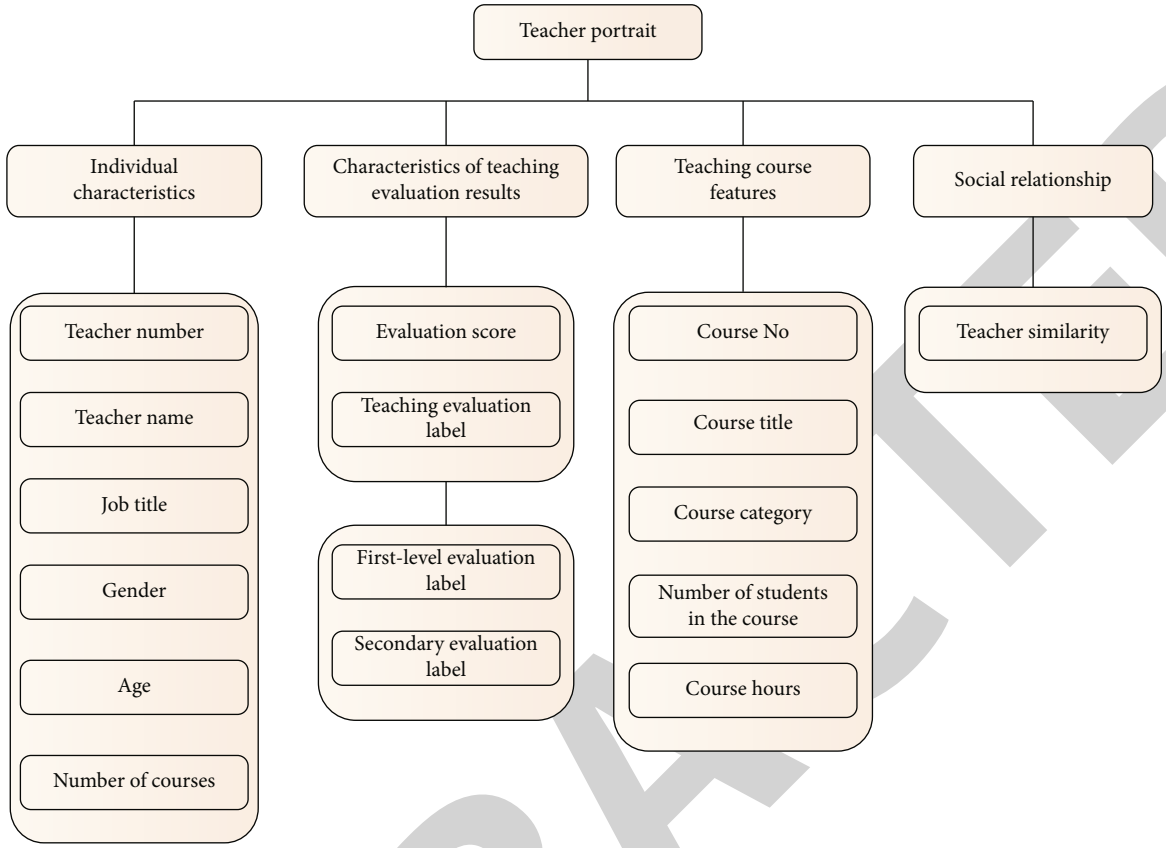

Figure 3: Multilevel teacher portrait model.

evaluation labels are constructed. So we can use EvaTag = <EvaTag_1, EvaTag_2, ⋯, EvaTag_{30} > to represent the label vector of teacher's secondary evaluation. The steps for the establishment of the teacher's second-level label vector extraction model are shown in Algorithm 2.

This article uses the Similarity between teachers to represent the attributes of teachers' social relationship model, namely Relation = (Similarity) in teacher portrait model. Wherein, the teacher's social relationship attribute vector is represented by Similarity, and the process of constructing Similarity vector of teacher portrait is as follows:

As can be seen from the above, Similarity = <Similarity_{a1}, Similarity_{a2}, ⋯, Similarity_{an} > is used to represent the similarity attribute of teachers, where Similarity_{ai} represents the similarity between teacher a and teacher i. The Similarity_{ai} vector proposed in this article is the similarity between teacher 's first-level evaluation label vector MainTag_a and teacher i 's MainTag_i. The calculation formula of similarity is shown in Formulas (1) and (2).

$$\text{Similarity}\left(\overrightarrow{MainTag_a}, \overrightarrow{MainTag_i}\right) = \cos\left(\overrightarrow{MainTag_a}, \overrightarrow{MainTag_i}\right), \tag{1}$$

$$\cos\left(\overrightarrow{Main\text{Mag}_a}, \overrightarrow{\text{MainTag}_i}\right) = \frac{\overrightarrow{MainTag_a} \cdot \overrightarrow{MainTag_i}}{\left|\overrightarrow{Main\text{Mag}_a}\right| \times \left|\overrightarrow{MainTag_i}\right|}. \tag{2}$$

MainTag_a represents the first-level evaluation label vector of teacher a, MainTag_i represents the first-level evaluation label vector of teacher i, and Similarity $(\overrightarrow{MainTag_a}, \overrightarrow{MainTag_i})$ represents the similarity between the first-level evaluation labels of teacher a and teacher i. EvaTag_i represents the second-level evaluation label vector of teacher a, EvaTag_i represents the second-level evaluation label vector of teacher i, and Similarity $(\overrightarrow{MainTag_a}, \overrightarrow{MainTag_i})$ represents the similarity of the second-level evaluation label vector of teacher a and teacher i. Similarity $(\overrightarrow{MainTag_a}, \overrightarrow{MainTag_i})$ is obtained by simple superposition of all the second-level teaching evaluation label vectors Similarity $(\overrightarrow{MainTag_a}, \overrightarrow{MainTag_i})$ to which the first-level teaching evaluation index belongs, and is finally processed by regularization.

4. Result Analysis

In the research of teacher portrait in this article, the research data comes from the educational administration information system of a university and the data of student evaluation teaching text in this article. The construction process of the whole teacher portrait is shown in Algorithm 3.

After the teacher portrait depiction in the second step, the formatted text data about the teacher portrait is formed. These text data are the teacher portraits in the teacher portrait library.

Name: Teacher secondary label vector model establishment steps
Input: a collection of teacher's student comments
Output: Keyword: Set of keywords
Methods and steps:
Step1: Text feature extraction

Word2Vec eigenvalue extraction algorithm is used to extract text features from the text set of students' comments on teaching, and the text feature vector space $D = <D(S_1), D(S_2), D(S_3), \cdots, D(S_n) >$ is constructed, among which, n represents the number of input text sets.

Step2: Generate text label vector

The text feature vector obtained in the first step is input into the algorithm of LDA model to calculate the classification probability of teachers on 30 second-level teaching evaluation labels, and the probability vector $P = \langle P_1, P_2, P_3, \cdots, P_n \rangle$ on the classification of second-level labels is obtained. The classification probability calculation formula of the document is shown in Formula (1).

$$P(C_j|D) = P(C_j) \times \prod_{i \in n} P(W_i|C_j) \quad (1)$$

$$P(W_i|C_j) = N(W_i \in C_j) + 1/N(C_j \in D) + 1 \quad (2)$$

In Formula (1), $P(C_j|D)$ represents the second-level teaching evaluation label, and the probability of C_j in the text feature vector space D of the teacher, that is, the proportion of times D of C_j in the teacher's teaching evaluation texts of all students. In Formula (2), $P(W_i|C_j)$ represents the frequency of W_i in a particular second-level evaluation label C_j, and $N(W_i \in C_j)$ represents the number of W_i in all evaluation texts contained in the j th second-level evaluation label. So in case you cannot compute if the denominator is 0, you have to add 1 to both the numerator and the denominator.

Step3: The calculation of label vector of secondary evaluation

The final second-level evaluation label vector can be obtained by simply adding all the word vectors of the 30 second-level evaluation labels obtained in the second step.

Algorithm 2: Steps for establishing the vector model of teacher's secondary label.

Name: Teacher secondary label vector model establishment steps
Input: teacher's individual characteristic information, teacher's course information, teaching evaluation index scoring data, student evaluation teaching text set
Output: Formatted teacher portrait text information
Methods and steps:
Step1: Data acquisition

By accessing the educational administration information system of a certain university, the individual characteristics of teachers and the course information of teachers are obtained. Then, the evaluation index score data and student evaluation text set are obtained through the student evaluation system of a certain university.

Step2: Depict the teacher's portrait

After a series of offline system processing, finally formed a formatted teacher portrait text.

Algorithm 3: Steps of teacher portrait construction.

In this article, text topic extraction is used to preliminarily test the effectiveness of the proposed algorithm. The method proposed in this article is based on Word2Vec word vector and LDA model (W2V_EVATAG_LDA), which is used to mine the semantic relationship between teaching evaluation text and teaching evaluation label. It can be regarded as the problem of extracting the topic vector of teaching evaluation text.

4.1. Experimental Environment. In this article, the experimental environment of the evaluation tag vector extraction experiment is divided into software environment and hardware environment. The specific experimental environment is shown in Table 6.

4.2. Data Set and Pretreatment. In this article, 22365 valid texts were randomly selected from the obtained data set of teaching evaluation texts as experimental data, including 2000 students' comments on 212 teachers, and a total of

Table 6: Configuration table of the experimental environment.

Software environment	
Operating system	Windows server 2008R2 Enterprise
Compiler	IntelliJ IDEA 2018.2 x64
Development language	JAVA
JDK version	JDK 1.8
Development kit	Hanlp
Hardware environment	
CPU	Intel(R) Core(TM) i7-7700HQ @ 2.8GHz
Memory	32GB
Hard disk	1024GB
Graphics	GTX 1060

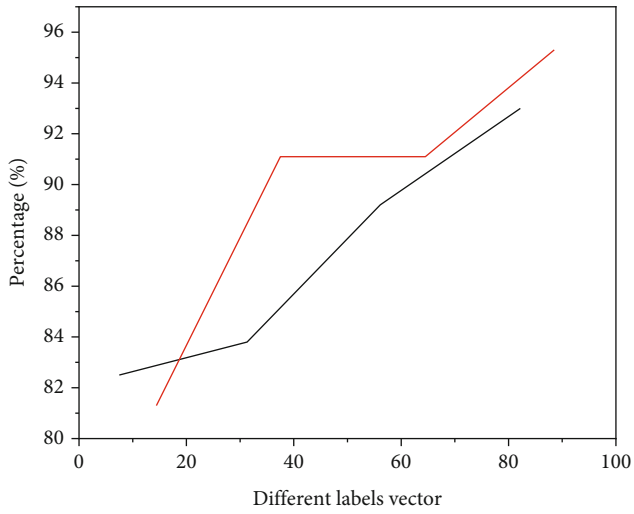

Figure 4: Comparison of extraction effects of different label vectors.

456 courses were reviewed. 500 of them are freshmen to seniors. Again, 70% of the experimental data were selected according to the data category as the training data of the label vector extraction model, and the other 30% as the test data [21]. Firstly, the experiment requires preprocessing of the teaching review text. First, jieba word segmentation in HANLP is used for word segmentation of the teaching review text, and then the stop word list released by Chinese Academy of Sciences is used to remove the stop words in the text.

4.3. Evaluation Indicators. In text topic vector extraction, Precision, Recall, and F1 values are generally used as the evaluation criteria for experimental results. The calculation formulas of Precision, Recall, and F1 are shown in Formulas (3), (4), and (5).

$$\text{Precision} = \frac{a}{a+b}, \tag{3}$$

$$\text{Recall} = \frac{a}{a+c}, \tag{4}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{5}$$

Formula (5) shows that the value of F1 is the harmonic mean of Precision and Recall. In this article, F1 value is used as the evaluation index for extracting the tag vector of text evaluation.

4.4. Analysis of Experimental Results

4.4.1. Accuracy of Different Tag Vector Extraction Methods. The method proposed in this article is based on Word2Vec text features and LDA model (W2V_EVATAG_LDA). The principle of the algorithm is to transform the space vector from high latitude to low latitude, and can reflect the main characteristics of the teaching text. In order to verify the effectiveness of this method, four text label vector extraction methods are used for comparative experiments [22]. They

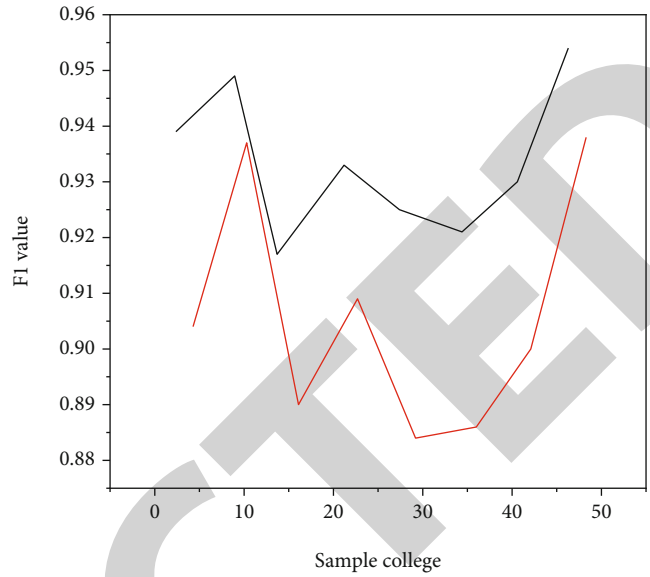

Figure 5: Comparison of label vector extraction effects of different college samples.

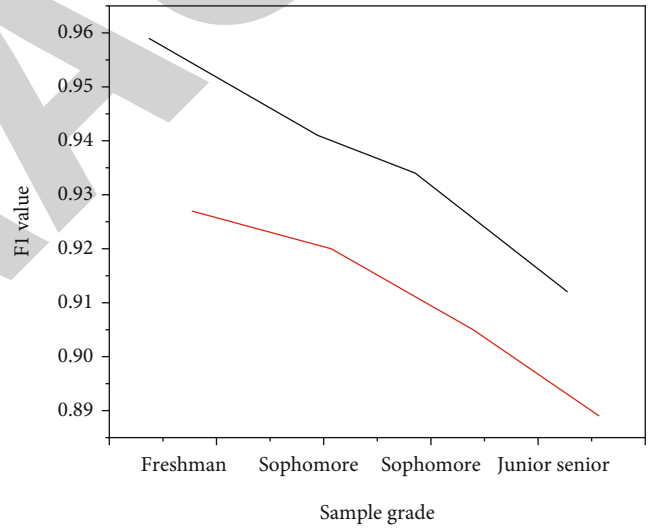

Figure 6: Comparison of label vector extraction effects of samples of different grades.

are tag vector extraction method based on Word2Vec model, tag vector extraction method based on one-hot word vector combined with LDA model, and tag vector extraction method based on Glove word vector combined with LDA model. Since the number of second-level evaluation labels is 30, the number of topics in the LDA model is set to 30. The experimental results are shown in Figure 4.

It can be seen from Figure 4 that the label extraction method proposed in this article is better than the label vector extraction method based on Word2Vec model, the label vector extraction method based on one-hot word vector combined with LDA model, and the label vector extraction method based on Glove word vector combined with LDA model. The validity of the label extraction method is proved [23].

Compared with other methods, Word2Vec model method has the worst effect on extracting tag vectors from text. This method does not consider the existence of multiple tags in the text and only represents the semantic features of the text context. The label vector extraction method based on one-HOT word vector combined with LDA model has a significant increase in accuracy. LDA model adopts word bag model, which expresses the potential semantic relationship between words and documents to a certain extent [24]. The content of the evaluation text is generated according to the evaluation tag, which indicates that the evaluation tag vector in the text can well represent the main semantic features of the text. The accuracy of tag vector extraction method based on Glove word vector and LDA model is higher than that of the previous two methods, indicating that word vector training by using the co-occurrence matrix between the statistical information of corpus and words can improve the accuracy.

4.4.2. Accuracy of College-Based Label Vector Extraction Method. In the teaching activities of colleges and universities, the teaching styles of different colleges are also affected by the differences in the teaching curriculum systems. According to definition 1, the accuracy of tag vector extraction method in evaluation texts of different colleges was calculated, and the Glove+LDA evaluation tag extraction method was used for comparison. The experimental results are shown in Figure 5.

As can be seen from Figure 5, the F1 values extracted by the model in this article are all higher than those extracted by the Glove+LDA method in the evaluation teaching label vector from the evaluation teaching texts of different colleges. Two schools, the School of Foreign Languages and the School of Accounting, had F1 scores of more than 94%. Both colleges are liberal arts colleges, indicating that students of liberal arts colleges write more standardized teaching evaluation texts, and the F1 value extracted from teaching evaluation labels is higher. The F1 value extracted from the evaluation labels fluctuates in the evaluation text data of different colleges, among which the school of Statistics has the lowest value (91.7%) and the school of Foreign Languages has the highest value (95.8%). The reason for this is that students from different colleges spend different amounts of time filling out their teaching evaluations. It can be seen that students' attitude towards writing teaching evaluation text may be related to the curriculum system of each college, which will have a certain impact on the effectiveness of extracting teaching evaluation label vector [25, 26].

4.4.3. Accuracy of Grade-Based Label Vector Extraction Method. Its purpose is to show the effect of extracting tag vector from students of different grades, that is, the influence of teaching text of different grades on extracting tag vector. According to definition 2, calculate the F1 value extracted from the evaluation label vector in the evaluation text of different grades, and the experimental results are shown in Figure 6.

As can be seen from the figure above, the algorithm in this article has a higher F1 value extracted from the teaching evaluation label vector in the teaching evaluation texts of different grades. F1 values showed a trend of gradient decline with the increase of grade, and the decreasing range became bigger and bigger. The reason may be that the quality of assessment texts will decline with the improvement of grades.

5. Conclusion

This article explains the teacher user portrait in the teaching ability diagnosis auxiliary system, and studies several key problems in the teacher portrait in detail, including the index system design of teacher portrait, teacher portrait model design generation. And the corresponding countermeasures are given. The combination of the teaching evaluation label system on the teacher portrait makes the constructed teacher portrait more accurate and effective, and provides a comprehensive and effective data model for the recommendation strategy of teaching ability improvement methods. The W2V_EVATAG_LDA tag extraction method proposed in this article combines the theme feature, semantic feature, local feature, and global feature of the text to extract the tag vector of the text. Through comparative experiments, it is proved that the proposed method is effective in extracting the text represented by multiple evaluation labels.

Data Availability

The data obtained by the author's own experiment.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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